Mapping poverty with remote sensing and other Big Data sources

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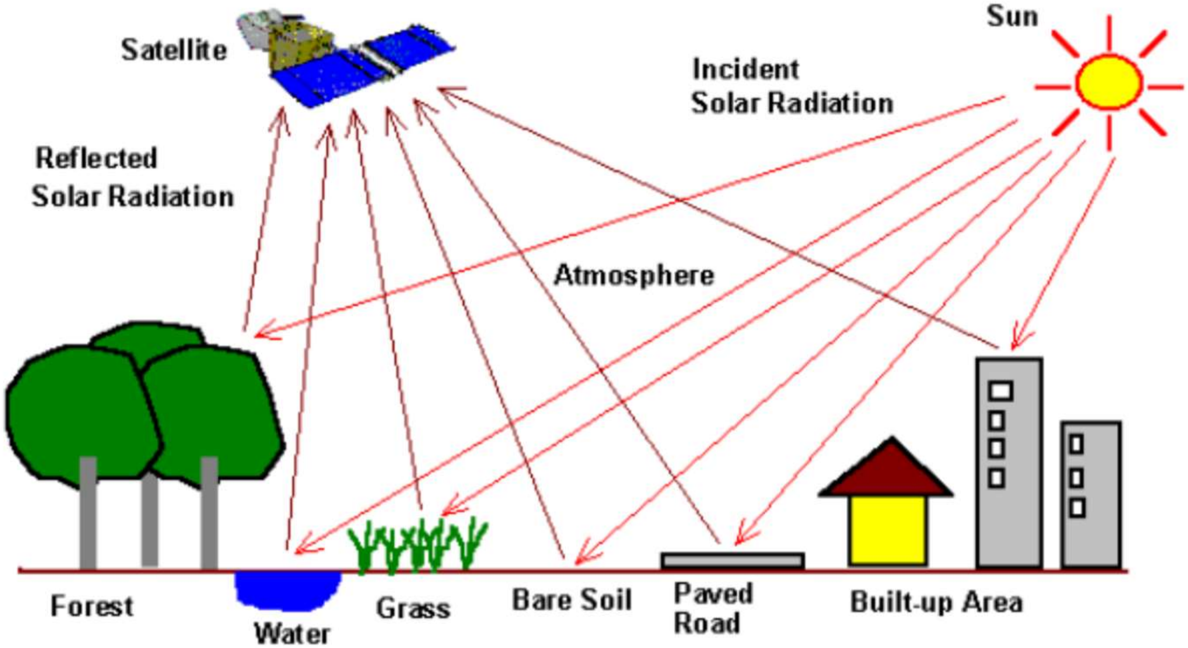
The Rationale

- Availability at national level on poverty is dramatically scarce worldwide
- From the WB WDI database: poverty gap and headcount at 5.50 USD is available only for around **29%** of data points in the last twenty years and **24%** for NPL: these are less than **10%** for the 20 ESCWA MCs
- The information at the disaggregated level (i.e. sex and geographic area) is practically unavailable
- Therefore, the motto of ‘leaving none behind’ appears as a mere daydream if it is not accompanied by specific actions aimed at improving data quality and availability

The Rationale

- Main issues
  - not all countries conduct household surveys
  - high data collection and processing costs
  - lack of timeliness in data availability
  - different timing and frequency of data collection
  - uncertainty in the survey cycle
  - lack of inter-comparability of surveys among countries
  - different impacts of measurement errors

Remote Sensing



Views from the Above During Night

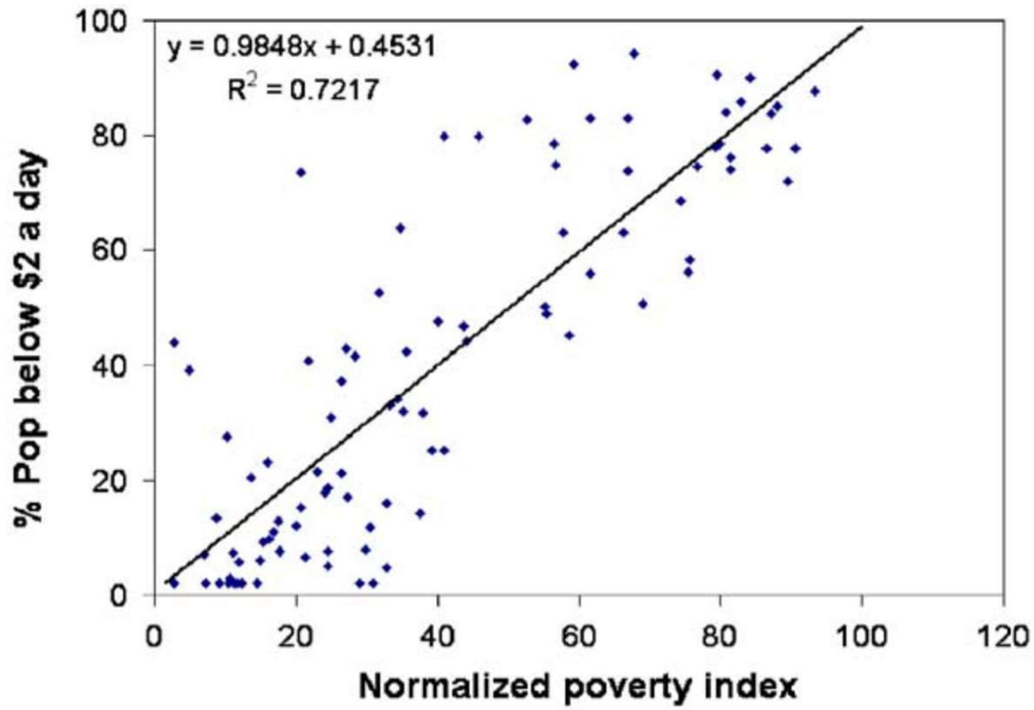
Remote Sensing During Nights

- Intensity of night lights linked by literature to:
  a) GDP per capita, Prices, PPP (+); ECON.
  b) Poverty rates (-); SOCIAL
  c) Population and migration flows (+); DEMOGR.
  d) Emissions, pollution, land degradation etc. (+); ENVIRON.
  e) Others (+,-), i.e. Wars, Smuggling,
  Informal activities, Tourism, Urbanization

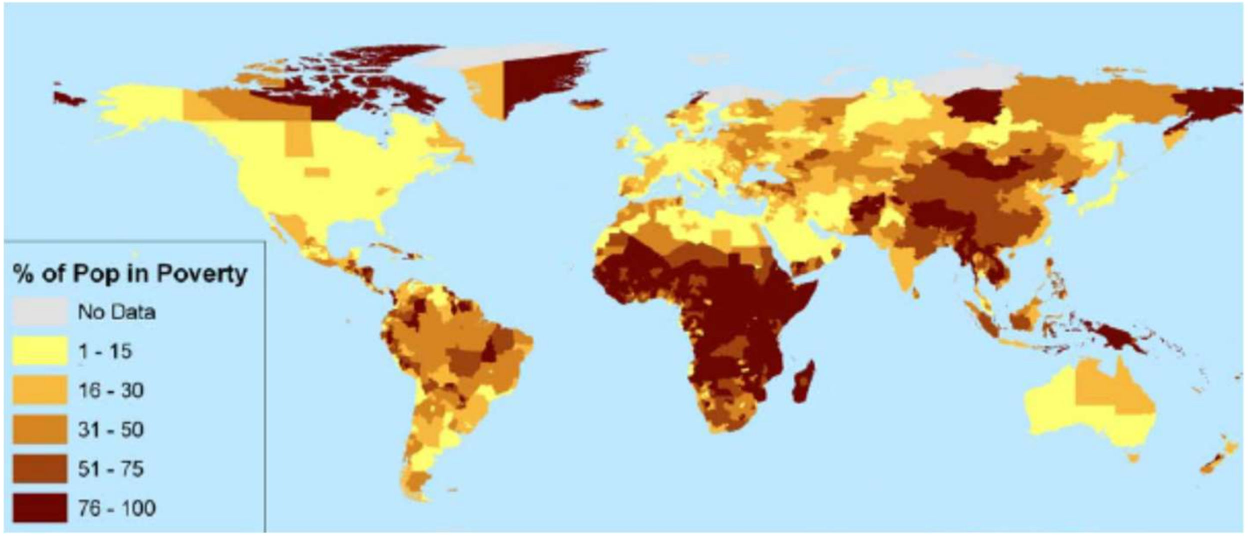
Application to Poverty

- Seminal paper by Elvidge et al. (2009)
- Use LandScan (source for Population annual data) and DMSP-OLS data of NASA (lights during night), both at 1 sq km resolution
- Derive a Poverty Index given by $PI = \frac{Pop}{NL}$
- Obtain a calibration between PI and official poverty rates drawn from WDI, which is then applied to obtain maps of poverty

Application to Poverty



Application to Poverty



Our Applications to Poverty

- **With fractional (unbalanced) panel-data model**: to obtain yearly maps of poverty rates in the LAC region …
- … at virtually 1 square km using DMSP-OLS images …
- … where official data are available only for some scattered years, and mostly at national level

Our Approach

- Fractional response (unbalanced) panel-data model

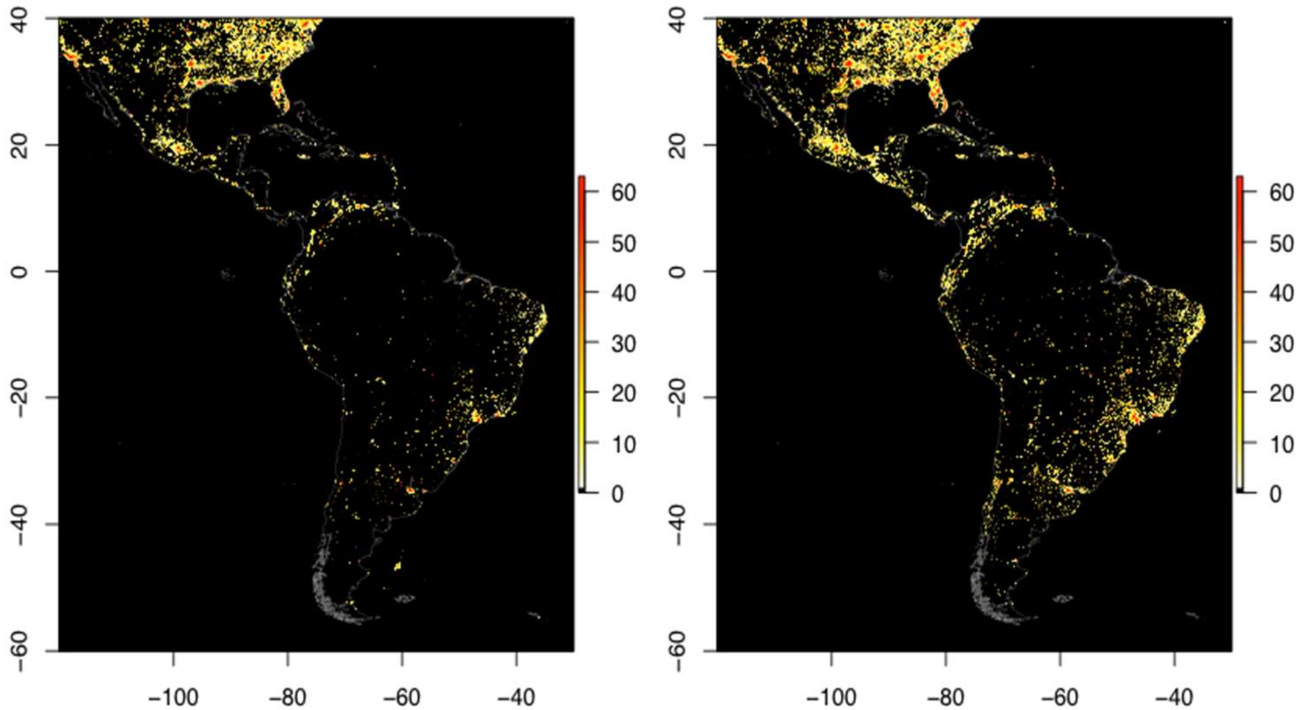
$$y_{it} = G(\boldsymbol{\theta}'\boldsymbol{x}_{\boldsymbol{it}} + \alpha_i + \gamma_t + \epsilon_{it})$$

- Exogenous variables are constructed only with observed night lights and population

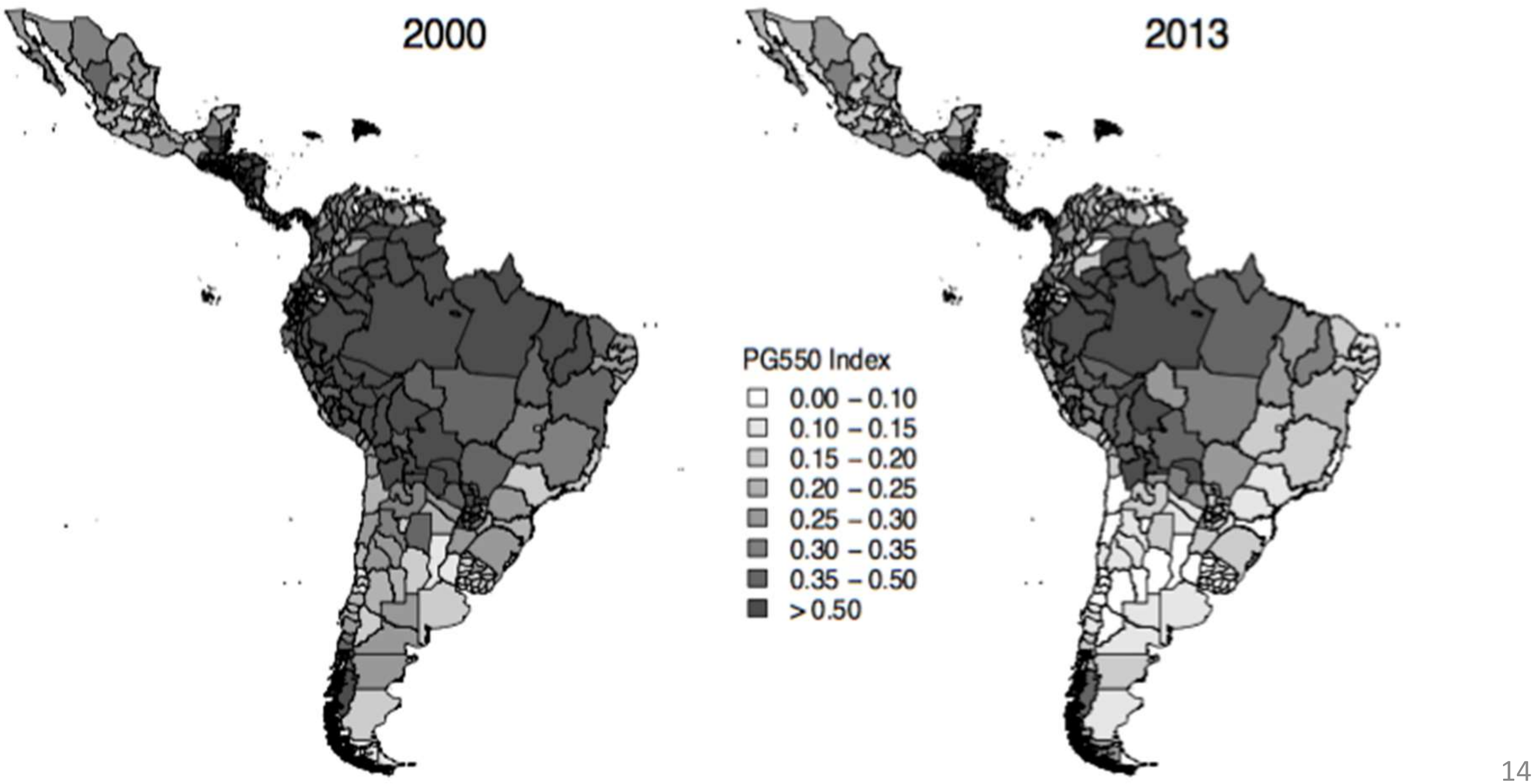
Our Approach

- Candidates exogenous:
  - Standard measures of lights (sum and mean, and the corresponding per-capita values)
  - Dispersion measures (the Gini and the Bonferroni indices, the mean log deviation, the inter-quintile diference as well as the standard deviation of lights)
  - Measures of urbanization, as proxied by night lights intensities
  - Population density
- Estimation of panel model at national level, and application of coefficients to night lights indicators observed at finer geographical detail, ideally 1 sq. km (strong assumption: no MAUP)

Application: Night Lights in LAC, 1993 (left) & 2013 (right)



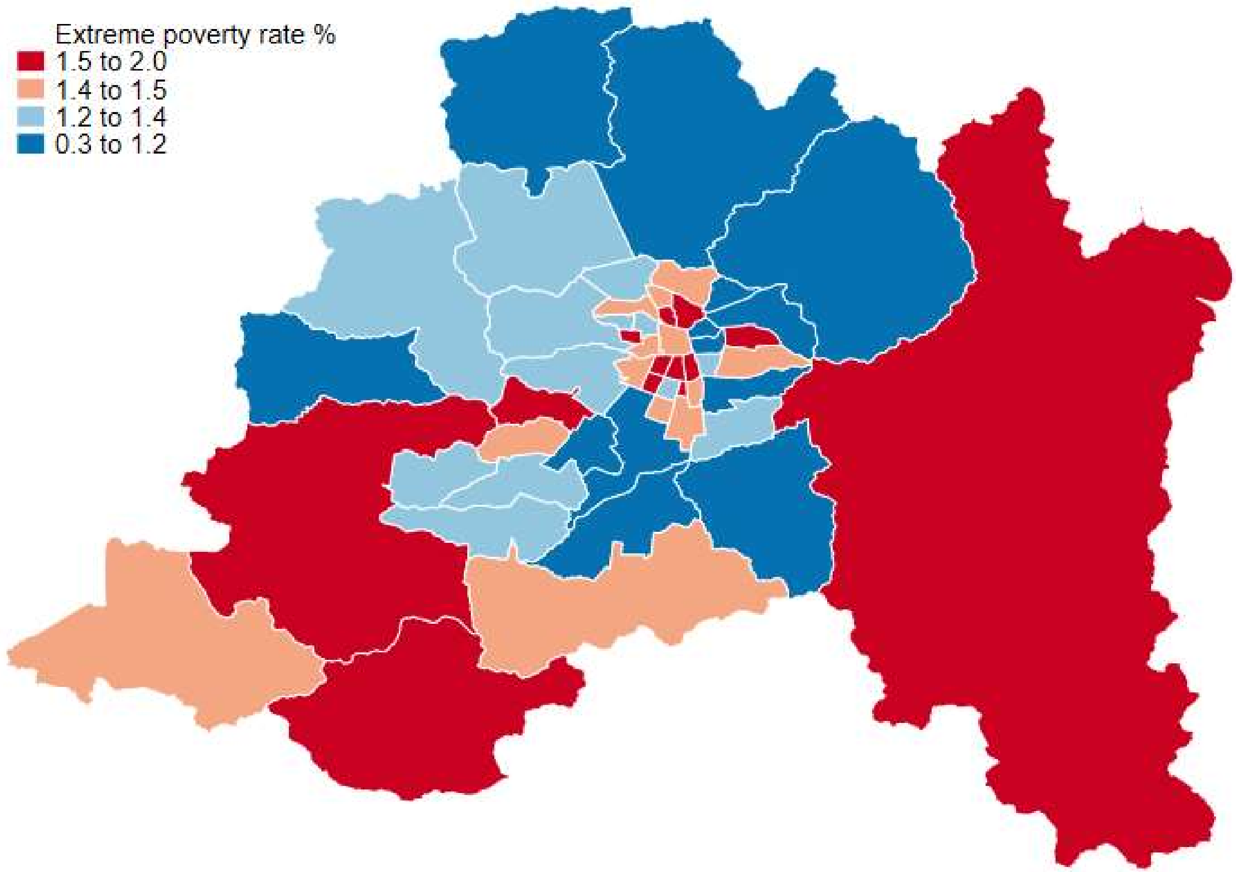
Application: Poverty Gap in LAC



Another Application of Night Lights

- **With fractional multinomial logit models and night lights**: to obtain monthly poverty maps of Chile (extreme, non-extreme and non poverty) …
- … at virtually 0.5 square km, with VIIRS satellite data …
- … where official data are available every 2-5 years and cover only part of municipalities of Chile

Applications: Poverty rates in Santiago, Chile



Applications of Night Lights with Other BD

- Jean et al. (2016) use survey and satellite day-and-night lights from five African countries - Nigeria, Tanzania, Uganda, Malawi, and Rwanda - to show how a convolutional neural network can be trained (machine learning) to identify image features that can explain up to 75% of the variation in local-level economic outcomes. The method, which requires only publicly available data, could transform efforts to track and target poverty in developing countries
- Steele et al (2017) use overlapping sources of remote sensing, mobile operator call detail records and traditional survey-based data from Bangladesh to provide a systematic evaluation of the extent to which different sources of input data can accurately estimate different measures of poverty

Conclusions

- Spatially disaggregated maps of poverty indicators, especially if updated on an annual or higher frequency, would be extremely beneficial for tracking the effectiveness of poverty-reduction efforts in specific areas, evaluating the consequences of natural disasters, conflicts or other general policy purposes
- Satellite images in the form of night lights could help in better understanding poverty and its space-temporal dynamics
- These information could be combined with traditional survey or census sources, as well as other Big Data sources, to better understand poverty developments
- Areas for further work might include cost-benefit evaluations of these combined use of official and Big Data sources, as well as evaluation of impacts of MAUP on small area estimation

Some References

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THANK YOU

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